TAT CHAN, CHAKRAVARTHI NARASIMHAN, and QIN ZHANG*

In this article, the authors offer a methodology to decompose the effects of price promotions into brand switching, stockpiling, and change in consumption by explicitly allowing for consumer heterogeneity in brand preferences and consumption needs. They develop a dynamic structural model of a household that decides when, what, and how much to buy, as well as how much to consume, to maximize its expected utility over an infinite horizon. By making certain simplifying assumptions, the authors reduce the dimensionality of the problem. They estimate the proposed model using household purchase data in the canned tuna and paper towels categories. The results from the model offer insights into the decomposition of promotional effects into its components. This could help managers make inferences about which brand's sales are more responsive to stockpiling or increase in consumption expansion and how temporary price cuts affect future sales. Contrary to previous literature, the authors find that brand switching is not the dominant force for the increase in sales. They show that brand-loyal consumers respond to a price promotion mainly by stockpiling for future consumption, whereas brand switchers do not stockpile at all. The authors also find that heavy users stockpile more, whereas light users mainly increase consumption when there is a price promotion.

Keywords: decomposition of promotional effects, dynamic structural model, flexible consumption, consumer heterogeneity

Decomposing Promotional Effects with a Dynamic Structural Model of Flexible Consumption

It is well known that store-level sales respond positively to short-term price promotions. Because different households respond to promotions differently, researchers have developed household-level models to understand the heterogeneity in purchase behavior. Following the seminal work of Guadagni and Little (1983), researchers (e.g., Bell, Chiang, and Padmanabhan 1999; Bucklin, Gupta, and Siddarth 1998; Chiang 1991; Chintagunta 1993; Gupta 1988) have explored the effects of price promotions using household scanner data and have decomposed the short-term effects into brand switching, purchase acceleration, and an increase in purchase quantity, with an increase in purchase quantity typically arising out of stockpiling behavior by households. All this research has assumed that the consumption rate of households is invariant to changes in prices. However, recent research has shown that households' consumption rates are also affected positively by price promotions (Ailawadi and Neslin 1998; Bell, Iyer, and Padmanabhan 2002; Sun 2005). The increase in consumption rate could be due to cross-category substitution as well as to a desire to consume more in the category. The latter effect may be caused by an income effect due to a lower price or may simply be induced by having a larger inventory. The drivers of the increase in sales due to a temporary price promotion need to be identified to understand the impact on manufacturers' and retailers' profits. For example, if the increase in sales is primarily due to an increase in consumption, both manufacturers and retailers might be better off from a tem-

*Tat Chan is Associate Professor of Marketing (e-mail: Chan@wustl.edu), and Chakravarthi Narasimhan is Philip L. Siteman Professor of Marketing (e-mail: Narasimhan@wustl.edu), Olin School of Business, Washington University in St. Louis. Qin Zhang is Assistant Professor of Marketing, School of Management, University of Texas at Dallas (e-mail: Zhangq@utdallas.edu). The authors are listed in alphabetical order. They thank the late Dick Wittink for his encouragement and wisdom, as well as the two anonymous *JMR* reviewers, participants at the Second Quantitative Marketing and Economics conference, and Scott Neslin for their excellent comments and suggestions. Sunil Gupta served as associated editor for this article.

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porary price promotion. If the effect is mostly brand switching, the manufacturer of the promoted brand is better off, but the retailer may or may not be. If the increase in sales comes mostly from stockpiling, the impact on profitability is ambiguous for both the manufacturer and the retailers, and further investigation is needed (Van Heerde, Leeflang, and Wittink 2004). Furthermore, if households that have a high preference for a particular brand stockpile the product for future use, it represents a loss in profits to the manufacturer. Similarly, if households that already have a high consumption level stockpile rather than expand their consumption, this again could represent a loss in profits. Thus, modeling flexible consumption in household behavior is important because, otherwise, an increase in sales may erroneously be attributed to other factors, resulting in misleading implications for manufacturers and retailers.

The foregoing discussion identifies two important research issues that need to be addressed. First, a model of household behavior in which consumption can be flexible based on external environment (e.g., prices, display, feature advertisements) and internal resources (e.g., income, inventory holding costs) should be developed to quantify the sources of increase in sales of a product due to temporary price promotions. Second, the differences in household behavior (e.g., increasing consumption, brand switching, stockpiling) based on brand preferences and overall usage rates need to be incorporated to identify correctly which households respond in what way to temporary promotions. Such a model has potential implications for managers deciding whether to offer any promotions, in what form they should be offered, and to whom they should be potentially targeted. Our goal in this article is to develop a household-level model that enables us to draw inferences to address these important questions.

We develop a dynamic structural model of a household that maximizes discounted utility from its consumption in a category. Consumption in each period is endogenous and is based on current marketing mix, inventory levels, preferences, and the household's expectations about future prices. In deciding whether to buy today, a household trades off inventory cost against the opportunity cost of buying the product in the future at a possibly higher price. Our model incorporates heterogeneity across households in inventory cost, price sensitivity, and underlying preferences. We propose a solution to overcome the dimensionality problem in our dynamic optimization model by imposing some simplifying assumptions. We apply our model to household-level scanner panel data in the canned tuna and paper towels categories.

We run simulations using the estimates from our model. We are able to decompose the total effect of a price promotion into its components of increase in consumption, brand switching in current and future periods, and stockpiling. Our analysis yields several notable insights. First, contrary to what is shown in most previous literature (e.g., Chiang 1991; Gupta 1988; Sun 2005), brand switching is not the dominant effect.[1] Second, for larger-share brands, the majority of a promotion-induced sales increase is attributed to stockpiling. Third, for smaller-share brands, the consumption effect is greater. Furthermore, we show that a household's brand preference has a significant impact on its stockpiling and flexible consumption behavior. Brand loyals mainly respond to a price promotion by stockpiling, whereas brand switchers do not stockpile. We also find that heavy users stockpile more for future consumption, whereas light users have a larger consumption increase under the price promotion. These findings have important implications for pricing and promotion strategies for manufacturers and retailers.

We organize the rest of the article as follows: In the next section, we describe related research and position our contribution with respect to this literature. Following this, we describe our dynamic structural model. Then, we discuss the data and details of our model. We also discuss the results of policy simulations and then provide some suggestions to managers based on our findings. Finally, we conclude with some extensions and directions for further research. Technical details of the estimation appear in the Web Appendix (http://www.marketingpower.com/jmraug08).

LITERATURE REVIEW AND CONTRIBUTIONS

Gupta (1988) was the first to decompose the promotional responses into brand switching, purchase (incidence) acceleration, and stockpiling effects using household-level data in the coffee category. He found that the dominant force was brand switching, accounting for 84% of the change in response, whereas purchase acceleration accounted for 14% and stockpiling accounted for 2%. Similar results were reported in Chiang (1991) and in Bell, Chiang, and Padmanabhan's (1999) cross-category study. Van Heerde, Gupta, and Wittink (2003) propose a different decomposition measure based on unit sales. Using the same data set as Gupta (1988) but at the store level, they find that only 33% of the unit sales increase is due to brand switching. Sun, Neslin, and Srinivasan (2003) find that the brand-switching elasticities are overestimated in reduced-form models, and to correct for this bias, they develop a dynamic structural model that accommodates consumers' forward-looking behavior under promotion uncertainty. These studies assume that a household's consumption rate is a constant and does not change as a result of price reduction. Van Heerde, Leeflang, and Wittink (2004) propose a regression model to decompose the store-level sales increase due to price promotions into cross-period (stockpiling), cross-brand (brand switching), and category expansion (consumption) effects. They find that, on average, each effect accounts for one-third in the four categories (tuna, tissue, shampoo, and peanut butter) they examine. Such store-level models provide insights into aggregate effects of price promotions but lack the advantages of household-level models that can explicitly account for observed and unobserved household heterogeneity in inventory cost, price sensitivity, and underlying preferences. These models may suffer from the "overparameterization" problem if the intention is to estimate cross-substitution patterns among many products. The proposed household-level model enables us to explore the differences in promotional responses across households even when there are many products in the choice set. Thus, we add to this literature by documenting the link between

[1]Our finding is consistent with those of Erdem, Imai, and Keane (2003), Van Heerde, Gupta, and Wittink (2003), and Van Heerde, Leeflang, and Wittink (2004). Ailawadi and colleagues (2007) find a strong consumption effect, which is also consistent with our findings.

promotional responses, especially changes in consumption, and household behavior.

A stream of literature models flexible consumption under price uncertainty using dynamic structural models based on household-level scanner data. Erdem, Imai, and Keane (2003) assume that households have an exogenous usage requirement in each period that is revealed to households after their purchases. The focus of their model is to study how inventory and future price expectations affect a household's purchase decisions. Sun (2005) models consumption as an endogenous decision and explores how price promotions affect this. Although we also model consumption as an endogenous decision, our focus on promotional effects and the decomposition leads us to several insights into how heterogeneity in brand preferences and consumption needs affects promotional responses. Moreover, to overcome the problem of the "curse of dimensionality" in dynamic programming due to a large choice set and a large number of panel members, we adopt a hedonic approach in modeling households' utility and invoke a few assumptions in households' decision processes to simplify the optimization problem.

MODEL

The Household's Problem

Let J be the number of products and H be the number of households in the market. Let y_{ht} be the J × 1 vector of household h's consumption quantity, let x_{ht} be a J × 1 vector of quantity purchased (both assumed to be continuous[2]), and let $u_{ht}(\cdot)$ be the utility function of consumption in period t.

At time t, household h decides whether to purchase, which product to purchase, how much to purchase, and how much to consume. Because products can be bought today for consumption in future periods, purchasing and consumption decisions in the current period will affect the inventory a household holds and change the implicit cost of future consumption. This creates a dynamic linkage among decisions across periods. Formally, we can state the dynamic planning problem at time t for household h as follows:

$$(1) \qquad \sup\{x_s, y_s\}E_t\left\{\sum_{s=t}^{\infty}\gamma^{s-t}\left[u_h(y_{hs}) - \lambda_h \times p_s'x_{hs} - c_h \times \left(\sum_{j=1}^{J} I_{hsj}\right)\right] \middle| \sigma_{ht}\right\},$$

$$\text{such that } I_{hs} = x_{hs} + I_{h,s-1} - y_{hs},\ x_{hs}, y_{hs}, I_{hs} \geq 0,$$

where p_s is a J × 1 vector of prices and I_{hs} is a J × 1 vector of the inventory levels of products in period s. We use λ_h to denote the marginal utility of income, c_h to denote the inventory cost of one standardized unit for household h, and γ to denote the discount factor that is common for all households. The term $E_t\{\cdot|\sigma_{ht}\}$ is the expectation operator conditional on the information set at t, σ_{ht}. The information set includes the inventory inherited from previous period, $I_{h,t-1}$, current and past marketing-mix variables (e.g., prices, features, displays), and household demographic variables. The endogenous decision variables in Equation 1 include $\{x_{ht}, x_{h,t+1}, \ldots; y_{ht}, y_{h,t+1}, \ldots\}$, where each component is a J × 1 vector, which is subject to the nonnegativity constraints.

The Indirect Utility Function

We use the hedonic approach to model a household's expected utility of consumption at some future period s evaluated at time t, s ≥ t, as follows:

$$(2) \qquad E_t u_h(y_{hs}) = (\Psi_{ht}'A'y_{hs} + \varphi_h)^{\alpha_h},$$

where A is a J × (C + J) characteristic matrix. The first C columns represent observable product attributes, such as brand names and flavors. The last J × J submatrix in A is an identity matrix, each diagonal element of which indicates the existence of the corresponding unobserved product attribute. The term Ψ_{ht} is a vector of household-specific and time-varying coefficients consisting of a C × 1 vector of household h's preferences for the observed attributes, ψ_{ht}, and a J × 1 vector of preferences for the unobserved attributes, ξ_{ht}; thus, $\Psi_{ht} = (\psi_{ht}|\xi_{ht})$. To keep the model tractable and not let the dimensionality explode, we do not model state dependence that might arise, for example, from variety-seeking behavior (see Seetharaman 2004) or the increase of repeat future purchases of promoted brands (see Ailawadi et al. 2007).

Given Ψ_{ht} and A, the terms α_h and φ_h determine the curvature and intercept of the marginal utility; the marginal utility with respect to consumption of product j is $\alpha_h \times (\Psi_{ht}'A_j') \times (\Psi_{ht}'A'y_{hs} + \varphi_h)^{\alpha_h - 1}$, where A_j is the jth row of the characteristic matrix, A. When the consumption is zero (i.e., $y_{hs} = 0$), it equals $\alpha_h \times (\Psi_{ht}'A_j') \times \varphi_h^{\alpha_h - 1}$. To guarantee diminishing marginal returns (i.e., concavity), α_h is restricted to be between 0 and 1. A household with a larger α is likely to consume more of the product category than a household with a smaller α. To allow for corner solutions (i.e., zero purchases), we restrict φ_h to be positive. Because it is difficult to identify both α_h and φ_h separately, we follow Kim, Allenby, and Rossi's (2002) recommendation and fix φ_h to be 1.

Let the household-specific coefficients in Equations 1 and 2 be $\theta_h \equiv (\alpha_h, \lambda_h, c_h)$, and let Z_h be a vector of demographic variables for household h; we assume that $\theta_h = g(Z_h, \theta_0)$, where $g(\cdot)$ is a vector of functions and θ_0 is a vector of parameters to be estimated. We discuss the model details subsequently.

The Proposed Solution to the Dynamic Optimization Problem

It is difficult to solve the dynamic optimization problem in Equation 1 when there is a large number of products in the choice set because of the curse of dimensionality. Previous empirical research has typically relied on either product aggregation or some other simplifying assumptions.[3] In our

[2]This is an approximation of the assumption that households only make discrete unit purchases. Kim, Allenby, and Rossi (2002) and Chan (2006) make similar assumptions.

[3]An example of the former is Sun (2005), who models purchases of only two products (aggregated at the brand level). An example of the latter is Hendel and Nevo (2006), who assume that the utility from a brand is derived entirely at the moment of purchase; thus, brand and quantity choices can be separated. Their assumption does not apply to our case,

application to the canned tuna category, we have 12 products with different combinations of product attributes. Product aggregation at the brand level will mask some cross-substitution patterns that exist at a more disaggregate level. We propose a solution to overcome this dimensionality problem. We assume that $c_h > 0$ for all h and that $p_{tj} > 0$ for all t and j. Let $\bar{p}_j$ be the highest price that product j could possibly charge. Because $\bar{p}_j - p_{tj}$ is finite for all t and j, we show in Web Appendix, Part A (see http://www.marketingpower.com/jmraug08), that there is a finite period, T, such that households do not expect to purchase at t and stockpile for the consumption in periods beyond t + T no matter how much inventory they are holding. Thus, we can rewrite the problem in Equation 1 to a finite horizon problem as follows (for simplicity, we omit the subscript h hereafter):

$$\text{(3)} \quad \sup\{x_s, y_s\} E_t \left\{ \sum_{s=t}^{t+T} \gamma^{s-t} \left[u(y_s) - \lambda \times p_s{}' x_s - c \times \left(\sum_{j=1}^{J} I_{sj} \right) \right] \middle| \sigma_t \right\},$$

$$\text{such that } I_s = x_s + I_{s-1} - y_s,\ x_s, y_s, I_s \geq 0.$$

In Equation 3, the optimal purchase and consumption levels in period t, $\{x_t^*, y_t^*\}$, are equivalent to the optimal solutions we would obtain from solving the infinite horizon problem in Equation 1. This implies that empirical researchers could start from a reasonably large number for T and solve this finite horizon problem.

To solve the finite horizon dynamic optimization problem, algorithms, such as the backward induction method, could be used. However, with a large number of state variables, the problem is still too complicated to be solved. Therefore, we impose the following two assumptions to further simplify the problem:

Assumption 1: A household consumes each product in its inventory proportionately. That is, given its inventory after the purchase at time t, $I_{t-1} + x_t$, the household plans to consume a proportion δ_s of its inventory in a future period s, where $s \geq t$.

Assumption 2: In period t, after observing current prices, a household updates its expectation about future prices. Specifically, we assume that after observing the current price of product j in period t, p_{tj}, a household updates its expected prices for product j for future periods as follows:

$$\text{(4)} \quad p^0_{tj} = p^0_{t-1,j} + \omega \times (p_{tj} - p^0_{t-1,j}),$$

where $p^0_{t-1,j}$ is the expected price before the household observes p_{tj}, p^0_{tj} is the updated expected price after p_{tj} is observed,[4] and ω is a parameter to be estimated. We expect that $0 < \omega < 1$.

With these two assumptions, we can simplify and rewrite Equation 3. In period t, under Assumption 1, given previous inventory I_{t-1} and current purchases x_t, the household's consumption at t, y_t, can be written as $\delta_t \times (I_{t-1} + x_t)$, and the total inventory, $\Sigma_{j=1}^J I_{tj}$, after the consumption is $(1 - \delta_t) \times \Sigma_{j=1}^J (I_{t-1,j} + x_{tj})$. For a future planning period s, because the expected future price is assumed to be constant over all planning periods (Assumption 2), the expected purchase at s, x_s, will be used only for consumption at s but not for stockpiling beyond s.[5] Thus, the consumption at s, y_s, can be written as $\delta_s \times (I_{t-1} + x_t) + x_s$, and the inventory at s can be written as $(1 - \delta_t - \ldots - \delta_s) \times (I_{t-1} + x_t)$. Thus, we can now rewrite Equation 3 as follows:

$$\text{(5)} \quad \sup\{x_t, \ldots, x_{t+T}; \delta_t, \ldots, \delta_{t+T}\} \Bigg(E_t u[\delta_t \times (I_{t-1} + x_t)] - \lambda\, p_t{}' x_t - c \times (1 - \delta_t) \times \sum_{j=1}^{J} (I_{t-1,j} + x_{tj})$$

$$+ \sum_{s=t+1}^{t+T} \gamma^{s-t} \times \Big\{ E_t u[\delta_s \times (I_{t-1} + x_t) + x_s] - \lambda p_t^{0}{}' x_s - c \times (1 - \delta_t - \ldots - \delta_s) \times \sum_{j=1}^{J} (I_{t-1,j} + x_{tj}) \Big\} \Bigg),$$

$$\text{such that } x_t, \ldots, x_{t+T}, \delta_t, \ldots, \delta_{t+T} \geq 0, \sum_{s=t}^{t+T} \delta_s = 1.$$

A comparison of Equation 5 with Equation 3 indicates that (1) the space of consumption decisions is reduced from $J \times (T + 1)$ to $1 \times (T + 1)$ and (2) the purchase in period s, x_s, affects only the expected consumption in that period and does not affect the inventory. Finally, the future expected price at s, p_s, is the same for all planning periods and is equal to p^0_t, which is the expected price formed in period t.

Note that though Assumptions 1 and 2 vastly simplify the dynamic programming problem, they impose some restrictions on the households' consumption and price expectations. Subsequently, we examine the implications of these assumptions and compare them with those in literature.

Assumption 1 describes how different products in the inventory are depleted. This assumption will affect our inference about the quantity and identities of household inventory over time and the expected utility of consumption. In Assumption 1, we assume homogeneity in the consumption of inventory across products. Erdem, Imai, and Keane (2003) and Hendel and Nevo (2006) make a similar assumption. Alternatively, we could assume that a household consumes its most favorite product first (Sun 2005) or that it consumes the inventory in the order the products were bought (i.e., the first-in, first-out rule). If the product category is highly perishable, the first-in, first-out rule would be the most reasonable assumption. However, this does not apply to our empirical applications in either the canned tuna or the paper towels category. The extent of the impact of this assumption would depend on the existence of

because the utility from product attributes in our model is derived at the moment of consumption.

[4]We assume that a household's expected price for product j before it observes the price in the first period in our data, $p^0_{j,0}$, is the regular price at the store this household most frequently visits. We define the regular price as the most frequently charged price in the store that is no less than its average price.

[5]This implicitly assumes that all products are perfectly dividable, which could pose a potential problem when applied to bulky products.

multiple products in household inventories. We further discuss this issue in the "Estimation Results" section.

Assumption 2 is about a household's formation of price expectations. Because expected price, p^0_{tj}, is assumed to be constant over all future planning periods, this assumption implies that at time t, the household expects that if it were to purchase at some time s > t, it would be only for consumption in period s. To buy at time t and hold the product until s, a household trades off the cost of holding inventory until s to the savings realized in period t. Prior research (e.g., Erdem, Imai, and Keane 2003; Sun 2005) has assumed that consumer expectations are fully rational. In such a case, the price-generating process would first be estimated from the data, and it would be assumed that households' expectations conform to this process. In our model, we do not make this assumption; we allow households to update their price expectations every time they observe a new price. This simplifies the dynamic optimization problem. However, if households buy from promotion to promotion and stockpile on each promotion just enough to last until the next promotion, our model will interpret such behavior as an outcome of high inventory cost or households' lowering their expectations (i.e., a lower value for p^0_{tj}). Thus, we would expect an unreasonably high estimate for the inventory cost from our estimation. In the "Estimation Results" section, we conduct a simulation to examine the impact on our conclusions when households expect periodic price promotions.

We provide further details on how to derive households' optimal decisions on whether to buy, which brand to buy, how much to buy, and how much to consume in Web Appendix, Part B (see http://www.marketingpower.com/jmraug08). We use the simulated method of moments in our estimation. The estimation procedure involves a nested algorithm for estimating θ—an "inner" algorithm that computes a simulated quantity purchased to solve the problem in Equation 5 for a trial value of θ and an "outer" algorithm that searches for the value of θ that minimizes a distance function between the simulated and the observed quantity. We repeat the inner algorithm until the outer algorithm converges. Details of the method are available in Web Appendix, Part B (see http://www.marketingpower.com/jmraug08), and identification issues related to the model estimation appear in Web Appendix, Part C (see http://www.marketingpower.com/jmraug08).

EMPIRICAL ANALYSIS

Data Description

We estimate the proposed model using the ACNielsen scanner panel data on canned tuna from January 1985 to May 1987 in Sioux Falls, S. Dak. We chose this category because canned tuna is easily storable and potentially a good candidate for stockpiling and flexible consumption. The sample consists of 74,795 observations from 1000 households drawn randomly from a panel of 3250 households. The selected households made 13,394 purchases during the sample period of 123 weeks and bought exclusively the 6.5-ounce size of canned tuna. We focus on purchases of 6.5-ounce cans because 94.7% of the total quantity sold is of this package. There are three main product attributes: brand, water or oil based, and light or regular in fat content (hereinafter referred to as "light" and "white," respectively). The grouping of the total 33 stockkeeping units (SKUs) by product attributes generates 12 product alternatives. The first 11 products are based on SKUs that share the same three attributes—brand name, water or oil, and light or white—and the last product consists of SKUs that belong to other brands. Henceforth, we use the term "product" to refer to one of these 12 alternatives. For each purchase occasion, we construct the price, feature, and display of the product bought as the weighted average over the SKUs that belong to this product alternative. The weight used is the quantity sold. For a product that a household does not purchase in a week, the price, feature, and display are constructed as the numerical average over all the SKUs that belong to the product alternative in the household's most frequently visited store. Web Appendix, Part D (see http://www.marketingpower.com/jmraug08), provides some summary statistics for these 12 products. The average number of units per purchase occasion was 2.15 units, and the average interpurchase time was 9.84 weeks.

The data set also contains the demographic characteristics of the households, such as family size, income, the employment status of the female head of household, and type of residency. We incorporate these variables in the estimation of our model. For the holiday effect on the purchase and consumption of tuna, we follow Chevalier, Kashyap, and Rossi's (2003) recommendation and incorporate the impact of the religious period of Lent, which occurs six weeks before Easter.

The Model Details

In our model, the parameter vector $\Psi_{ht} = (\psi_{ht}|\xi_{ht})$ represents the stochastic household preferences for product attributes. To simplify computation, we assume that ξ_{ht} ~ normal(0, σ^2_x) and i.i.d. over households and periods in our estimation. We use a random coefficient approach to model ψ_{ht}. Its first element, $\psi_{ht}^{[1]}$, represents the household consumption preference for tuna. We allow it to be affected by Lent; that is, $\psi_{ht}^{[1]} = \bar{\psi}^{[1]} + \varphi \times \text{HOLIDAY}_t + \eta_{ht}^{[1]}$, where HOLIDAY_t is an indicator of whether time t is in the weeks of Lent, $\eta_{ht}^{[1]}$ is a time-varying taste shock distributed as normal(0, σ^2) that is i.i.d. over households and periods, and $\bar{\psi}^{[1]}$ and φ are parameters to be estimated. For simplicity, we assume that φ is homogeneous across households.[6] Other elements of ψ_{ht}, $\psi_{ht}^{[k]}$, where k ≠ 1, represent household preferences for brands, water (versus oil), and light (versus white). To simplify the analysis, we assume that these parameters are time invariant; that is, $\psi_{ht}^{[k]} = \bar{\psi}^{[k]} + \eta_h^{[k]}$, for all t, where $\eta_h^{[k]}$ is again distributed as normal (0, σ_k^2) and $\bar{\psi}^{[k]}$ is a parameter to be estimated. To reduce the computational burden, we assume that preferences for product attributes are uncorrelated. Furthermore, given that the market share of products with the attribute of "white" is extremely small (.5%), it is difficult to identify, for example, the correlation in preferences between water and light.

We restrict the parameter α_h in Equation 2 to be between 0 and 1. To allow for unobserved household heterogeneity, we assume that there are K discrete segments with different values of α, but within each segment, we allow α to vary with family size, which seems to be the only demographic

[6]We estimate an alternative model that allows heterogeneity in φ and assumes it to be normally distributed. All parameter estimates are close to the results we report in Table 1. The results are available on request.

variable in our data that could affect the consumption rate. For household h that belongs to type k, the specification is as follows:

$$(6)\qquad \alpha_{h,k} = \frac{\exp(\alpha_{0k} + \alpha_{1k} \times \text{FMY}_h)}{1 + \exp(\alpha_{0k} + \alpha_{1k} \times \text{FMY}_h)},$$

where FMY_h represents the family size of household h and α_{0k} and α_{1k} are parameters to be estimated. Unlike the heterogeneity specification for ψ_{ht}, we assume that the heterogeneity for α_h has a latent structure. For example, if we assume that α_{0h} and α_{1h} are normally distributed, after the transformation in Equation 6, α_h would be a nonstandard distribution, which we find difficult to justify. Latent structure specification seems to be a more robust assumption in this case.

Households are likely to be heterogeneous in the price sensitivity parameter λ_h. We follow the extant empirical literature and assume that price sensitivity is a function of the household income level. Moreover, a household with a working female head may be less price sensitive than those without. Thus, we follow Chan's (2006) recommendation and use the following specification for λ_h:

$$(7)\qquad \lambda_h = \frac{1}{\left[\frac{\ln(\text{INCOME}_h)}{\ln(\min \text{INCOME})}\right]^{\lambda_1} \times \text{EMPLOY}_h^{\lambda_2}},$$

where INCOME_h is the income of household h, minINCOME is the minimum household income in data, and EMPLOY_h is the employment status of the female household head. This specification restricts the parameter λ_h to be positive.[7] A positive value for λ_1 or λ_2 implies that households with a higher income or a working female head are less price sensitive. Because the product category preference ($\bar{\psi}^{[1]}$) is estimated in the model, we normalize the price sensitivity of a household with the minimum income level and nonworking female head to 1, as Equation 7 implies. In addition, because of this normalization, the unobserved heterogeneity in λ_h cannot be identified.

Inventory cost may be affected by a household's income level (more affluent households may have larger houses and, thus, lower inventory cost) and the residence type (living in a single family home may imply lower inventory cost than living in an apartment). To allow for the heterogeneity in inventory costs, c_h, among households, we assume the following:

$$(8)\qquad c_h = c_0 + c_1 \times [\ln(\text{INCOME}_h) - \ln(\text{minINCOME})] + c_2 \times \text{RESIDENCE}_h,$$

where RESIDENCE_h is the residence type of the household h (1 if household h lives in a single family house and 0 if otherwise). We do not expect other demographic variables to have significant impacts on the inventory cost. Because a household's consumption, inventory, and price-updating process are not observable in the data and must be inferred from its purchases, it is difficult to identify the unobserved heterogeneity in c_h and ω in Equation 4. Therefore, we chose to allow for unobserved heterogeneity only in consumption preferences (i.e., in ψ_h and α_h). Incorporating unobserved heterogeneity in c_h and ω would add confounds in the estimation.

We assume that in-store marketing activities, such as displays and features, change the marginal utility of consumption by a constant amount, β_d and β_f, respectively. We further assume that a household's expected utility at some future period s is affected by the current displays and features. This seems to be a reasonable assumption given that we model the current purchasing decisions at time t. Thus, we can rewrite the indirect utility function in Equation 2 to include effects of displays and features as follows:

$$(9)\qquad E_t u_h(y_{hs}) = (\Psi_{ht}'A'y_{hs} + \varphi_h)^{\alpha_h} + \beta_d \times \text{DISPLAY}_t'y_{hs} + \beta_f \times \text{FEATURE}_t'y_{hs},$$

where β_d and β_f are parameters to be estimated.[8]

We do not observe household h's inventory when it makes its first purchase in our observational period, $I_{h,0}$. We infer this from the estimation. Intuitively, if household h makes a purchase when the price in that period is high, it could indicate that its inventory is low. Therefore, we assume the following:

$$(10)\qquad I_{h,0} = \exp(\upsilon_h), \text{ and } \upsilon_h \sim \text{normal } [\rho \times (p_{h,1,j} - p_j^a), 1],$$

where $p_{h,1,j}$ is the observed price of the chosen product j when household h made the first purchase, p_j^a is the average price of product j over the entire sample period, and ρ is a parameter to be estimated. If ρ is negative, a higher first purchase price indicates a lower initial inventory.[9]

Finally, we fix the number of finite periods, T, to 12. Given that our estimated inventory cost per week (we discuss this in the "Estimation Results" section) is \$.02 and that the difference between the regular price and the minimum price for all products in our data is smaller than \$.15, our results should not change even if we increase the value of T. Note that for any household, inventory on hand may last for more than 12 weeks if the realized consumption is less than what is expected. This implies that when making the purchase decisions, households do not plan to stock up for more than 12 weeks.

Estimation Results

We report the results of the estimation in Table 1. StarKist and Chicken of the Sea are the two most preferred brands. On average, the attributes "water" and "light" also increase consumption utility. However, there is large heterogeneity in household preferences. For example, the mean preference for the category is –.12, with a standard deviation of .48. The negative mean preference is consistent with our data; most households buy tuna only occasionally. Similar heterogeneity also exists for preferences for other

[7]Alternatively, a linear specification with exponential transformation can be used.

[8]We do not model display and feature as observed attribute components in Matrix A for the following reasons: (1) Display and feature are time-varying attributes, whereas the observed product attributes we include in A are time invariant, and (2) if these two were included in Matrix A, the slope of marginal utility of consumption would vary with feature and display over time.

[9]Ideally, the initial inventory of a household should be defined as the inventory on its first store visit. However, in the data used for our empirical analysis, different households enter the data at different times, and we do not have information about their first store visits. Thus, we cannot estimate the initial inventory from the first store visits.

Table 1

ESTIMATION RESULTS FOR THE CANNED TUNA CATEGORY

Parameters	*Estimate*	*SE*
Tuna	–.12	.01
StarKist	3.01	.01
Chicken of the Sea	2.15	.01
3 Diamond	–2.87	.03
Control	–2.31	.03
Water	2.79	.01
Light	.35	.01
Feature	1.97	.01
Display	2.65	.01
Price × income	.001	.01
Price × employ	.02	.01
c_0 (inventory)	.02	.001
c_1 (inventory × income)	.0002	.001
c_2 (inventory × residence type)	–.0001	.004
α_{01} (power term intercept – Segment 1)	–1.97	.02
α_{02} (power term intercept – Segment 2)	–.0003	.01
α_{11} (power term family size – Segment 1)	–1.01	.02
α_{12} (power term family size – Segment 2)	–.16	.01
Probability of Segment 1	.80	.08
σ_1 (tuna)	.48	.01
σ_2 (StarKist)	2.94	.01
σ_3 (Chicken of the Sea)	3.68	.01
σ_4 (3 Diamond)	.47	.03
σ_5 (control)	.09	.03
σ_6 (water)	3.09	.01
σ_7 (light)	.48	.01
σ_8 (feature)	.27	.01
σ_9 (display)	.23	.01
σ (product-specific household preferences)	2.73	.01
ρ (initial inventory)	–2.19	.10
ω (price updating parameter)	.20	.01
Holiday effect	.04	.01
Function value	487.27	

product attributes. Household responses to marketing activities, such as feature advertising and store display, are significant and positive. Income does not affect price sensitivity, but if the female head of household is employed, the household is less price sensitive, which is consistent with prior research. The estimated average inventory cost of a can of 6.5-ounce tuna is $.02 per week, which is reasonable given its price. The unit inventory cost of a household is not affected by its income level or residence type. An explanation for this could be that because canned tuna is relatively easy to store, households do not run into space constraints caused by income or residency types.

The consumption level in our model is determined by the following:

$$\alpha_{h,k} = \frac{\exp(\alpha_{0k} + \alpha_{1k} \times \mathrm{FMY}_h)}{1 + \exp(\alpha_{0k} + \alpha_{1k} \times \mathrm{FMY}_h)}.$$

We assume two latent segments and estimate their α_0 and α_1, respectively.[10] The first segment, accounting for 79.9% of all the households, has a smaller value of α_0. This is the segment of light users of tuna. It seems counterintuitive that α_1 is negative for both segments, implying that smaller families have a larger consumption rate for this category. An explanation is that single households use tuna as a substitute for cooked meals and are likely to purchase it more. The negative ρ implies that if a household buys at a higher price during its first observed purchase, the household might have a lower starting inventory level. This is consistent with our intuition. The estimate of ω is .20 and significant. Its positive sign confirms our expectation. Because $0 < \omega < 1$, it implies that households adjust their expectations downward when they find the current prices to be lower than their prior expectations; however, the updated expected prices will be higher than the current prices. As we expected, Lent positively affects the consumption of tuna. During Lent, households consume more tuna as a substitution for meat.

An advantage of using the hedonic approach to model households' preferences for products is to reveal succinctly the substitutability across a large number of products. Without using the hedonic approach, to recover the cross-substitution patterns, we would need to estimate the whole variance–covariance matrix corresponding to the random coefficient preferences for 12 products. Here, we need to model only the distribution of household preferences for the major product attributes, which vastly reduces the dimensionality. We simulate cross-elasticities among the 12 products on the basis of our estimates and find some notable results. For example, for Chicken of the Sea/water/light, Chicken of the Sea/oil/light and StarKist/water/light are its close substitutes, whereas StarKist/oil/light is not (cross-elasticities are .16, .13, and .07, respectively). For StarKist/oil/light, StarKist/water/light and Chicken of the Sea/oil/light are equally substitutable (the cross-elasticities are .07 and .06, respectively). Chicken of the Sea/water/light and Chicken of the Sea/oil/light are more substitutable (.16) than StarKist/oil/light and StarKist/water/light (.07). This suggests that there is an interaction effect between brand name and other attributes on substitutability. These results should help managers make strategic decisions when they consider price promotions at the SKU level rather than at the brand level.

Using the estimation results, we calculate the predicted purchases of all 1000 households for each week. The correlation between the observed and the predicted purchases is .86. The correlations for the two products that have the largest market shares, StarKist/water/light and Chicken of the Sea/water/light, are .81 and .76, respectively. These findings suggest a high level of model fit with the data.

Note that Assumption 1 will affect the estimation results only if households in our data stockpile multiple products in their inventory. Our data show that only approximately 30% of the purchases involve an interpurchase time that is less than six weeks and a brand choice that is different from the one on the previous purchase. Unless households stockpile for more than five weeks, our results will not be sensitive to this assumption, and indeed, this appears to be the case from our estimation.

Next, we conduct a simulation to examine whether and how the estimates from our model will be biased when Assumption 2 is not valid. We first simulate the consumption and purchases of 100 hypothetical households in 100 weeks using traditional dynamic optimization techniques, under the assumption that all the households are forward

[10]We also estimated the model by assuming three latent segments. The model fit improves only marginally, and the estimates are similar to the two-segment model. The estimation results are available on request.

looking and correctly anticipate the discounting process. It is infeasible to solve a dynamic optimization model with 12 products because of the dimensionality problem; thus, we focus on Assumption 2's effect on stockpiling and consumption behavior in the simulation and abstract away its effect on brand-switching behavior. We assume that there is only one brand in the market and that households are only heterogeneous in their brand preferences. We further assume that in each week, the brand charges a regular price of $.80 with 80% probability and a promotional price of $.60 with 20% probability. The households correctly anticipate that there is a 20% chance of a promotion in every week. We estimate our model using the simulated data. Web Appendix, Part E (see http://www.marketingpower.com/jmraug08), shows the "true" parameters in the dynamic optimization model that we used to simulate the data and the estimation results from our model. The results show that our model recovers the true parameters, except the inventory cost, accurately. As we discussed previously, the biased estimate for inventory cost is due to our model ignoring households' full and correct expectations of periodic discounts. However, note that the estimated inventory cost from the data on tuna purchases is $.02, which does not seem unreasonably high, indicating that Assumption 2 may not be violated in our data.

We are more concerned about how the decomposition of promotional effects is affected when Assumption 2 is not valid. To address this issue, we calculate the decomposition of promotional effects for the true (dynamic optimization) model as well as that based on the estimates from our model. We assume a price cut of $.20 in the first week and a regular price for the following weeks. We report the comparison of the decompositions in Web Appendix, Part F (see http://www.marketingpower.com/jmraug08). The results show that though the total effect and its components from our model are lower than the corresponding values in the true model, the differences are relatively small considering the existence of estimation errors in finite sample data. Furthermore, the correlations between simulated and predicted purchases and consumption are .99 and .98, respectively, suggesting that our model recovers these quantities accurately. Thus, even if Assumption 2 is not valid, our results on the decomposition of promotional effects remain valid.[11]

Decomposing the Promotional Effects

To answer the questions we raised previously regarding the effects of price promotions on consumption, brand switching, and stockpiling, we conduct simulations using the estimates from our model.[12] In the simulations, we use the 1000 households in our estimation, and for each household, we draw ten random samples from the estimated distribution of the stochastic components in the utility function. We first simulate the purchases and consumption of these households when they face the regular prices for all products for T = 12 successive weeks. Then, we simulate the purchases and consumption for the same households over the 12 weeks when each product has a price discount of $.10 in the first week.[13] A comparison of the sales before and after the price cut enables us to decompose the effects of price promotions into increases in consumption, brand switching, and stockpiling. We define the total effect of a price cut as the sales increases in Week 1. That is,

$$(11)\qquad TE_j = \left\{ \sum_{h=1}^{10000} [x_{hj1}(p_j^1) - x_{hj1}(p^0)] \right\},$$

where p^0 is the price vector when all products charge their regular prices and p_j^1 is the price vector when product j has a price cut while other products remain at their regular prices.

We define the consumption effect as the difference in the total consumption in all 12 weeks before and after the price cut. Households could change their consumption rate as prices change as a result of the following effects: (1) there is a category substitution effect as households switch from consuming other categories, such as from meat to tuna; (2) having more inventory may induce households to consume more tuna than they usually do; and (3) there is an income effect due to price promotions.

Because prices change only in the first week in our simulation and because we assume that the household planning horizon is 12 weeks (i.e., households will not purchase in Week 1 and hold these purchases as inventory for future consumption beyond Week 12), the consumption effect is equal to the difference in the total quantity bought of all products in 12 weeks before and after the price cut. That is,

$$(12)\qquad \begin{aligned} CE_j &= \sum_{t=1}^{12} \sum_{h=1}^{10000} \sum_{k=1}^{12} [y_{hkt}(p_j^1) - y_{hkt}(p^0)] \\ &= \sum_{t=1}^{12} \sum_{h=1}^{10000} \sum_{k=1}^{12} [x_{hkt}(p_j^1) - x_{hkt}(p^0)], \end{aligned}$$

where $y_{hjt}(\cdot)$ and $x_{hjt}(\cdot)$ are household h's consumption level and purchase quantity for product j in period t.

We measure the brand-switching effect in all 12 weeks as the decrease in total sales of other brands (whose prices remain as their regular prices) as the focal product cuts its price in Week 1. We compute two components: brand switching that occurs in the first week (BS_{j1}) and that which occurs in later weeks (BS_{jL}). That is,

$$(13)\qquad \begin{aligned} BS_{j1} &= \sum_{h=1}^{10000} \sum_{k \neq j} [x_{hk1}(p^0) - x_{hk1}(pj^1)] \\ BS_{jL} &= \sum_{t=2}^{12} \sum_{h=1}^{10000} \sum_{k \neq j} [x_{hkt}(p^0) - x_{hkt}(p_j^0)]. \end{aligned}$$

[11]To check the sensitivity of household decisions to various specifications of price expectations, we also empirically estimate two other specifications: (1) $p_{tj}^0 = p_j^r + \omega \times (p_{tj} - p_j^r)$, and (2) $p_{tj}^0 = p_j^a + \omega \times [(p_{t-1,j} + p_{tj})/2 - p_j^a]$, where p_j^r is the regular price of product j and p_j^a is the average price of product j. Estimation results are similar to those we obtained from Equation 4, but these two models perform worse in data fit. The results are available on request.

[12]We cannot identify the store-switching effects in our model. Because households buy a basket of goods, to address this issue, we must study the purchasing patterns across multiple categories. This is a difficult task using our household-level data. Moreover, we suspect that the store-switching effect is not significant in this category, because the purchase of tuna usually accounts for a relatively small portion of total basket expenditure and is not a major factor in store choice decisions. If households switch from a store that is not in our data to a store that is in our data because of a price promotion, the increase in purchase is counted as an increase in consumption.

[13]We also conduct the simulations using a price discount of $.20, and the results are robust.

Brand switching in later weeks may exist when some households switch to buying j under price promotion in Week 1 and stockpile for later consumption; thus, they will buy less of other brands in later weeks. Note that because these households are paying the same prices for the other brands under p^0 or p_j^1, the consumption and stockpiling effects of the other brands are zero.

The difference between TE_j and the sum $CE_j + BS_{j1} + BS_{jL}$ is the residual component of a sales increase of product j that is neither from an increase in consumption nor from the substitution of other products in current and future weeks. This can only be due to the stockpiling effect (cross-period substitution in Van Heerde, Leeflang, and Wittink 2004), which comes from the behavior of households that would purchase product j under the regular price p^0 in later weeks but are taking advantage of the price cut in Week 1. Note that households that do not buy product j under p^0 but switch to product j under prices p_j^1 may also stockpile, but this effect is accounted for as brand switching (in later weeks) under our definition. Therefore, the stockpiling effect is as follows:

$$SP_j = TE_j - CE_j - BS_{j1} - BS_{jL}. \quad (14)$$

We can rewrite CE_j in Equation 12 as follows:

$$CE_j = TE_j + \sum_{t=2}^{12}\sum_{h=1}^{10000}[x_{hjt}(p_j^1) - x_{hjt}(p^0)] + (-BS_{j1}) + (-BS_{jL}). \quad (15)$$

Thus, combining Equations 14 and 15, we get the following:

$$SP_j = \sum_{t=2}^{12}\sum_{h=1}^{10000}[x_{hjt}(p^0) - x_{hjt}(p_j^1)]. \quad (16)$$

Because all prices remain at their regular levels after Week 1 in the decomposition using the simulated data, the total sales of product j from Week 2 to Week 12 after the price cut will not be greater than those before the price cut (i.e., $SP_j \geq 0$).

Decomposing the Aggregate Promotional Effects

Dividing the total effect of the price promotion in Equation 11 by the total unit sales of product j under the original (regular) price and further by the percentage of price change, we rescale the total promotional effects to help compare the effects among brands. We decompose the total effect into consumption, brand switching, and stockpiling by dividing Equations 12, 13, and 16 by the total unit sales of product j under the original price and then by the percentage of price change.[14] Table 2 shows the result of this decomposition.

First, the average consumption effect is 29%, the brand-switching effect is 28% (the brand switching in the first week accounts for 22%), and the stockpiling effect is 43%. Van Heerde, Leeflang, and Wittink (2004) report similar decomposition results from their store-level model for the same category (31%, 31%, and 38%, respectively). They further decompose the consumption effect (“category expansion effect”) into “cross-store effect” and “market expansion effect.” Because we do not model the store-switching behavior, we are not able to replicate their exercise. Compared with Sun’s (2005) results (i.e., 33%, 42%, and 25%, respectively), our consumption effect is similar, but the brand-switching effect is lower and the stockpiling-effect is higher.

Second, the effects are different between larger-share brands (i.e., StarKist and Chicken of the Sea) and smaller-share brands (i.e., 3 Diamond and the control):

1. Smaller-share brands have higher total promotional effects than larger-share brands. This is consistent with prior findings (Chintagunta 1993; Kopalle, Mela, and Marsh 1999).
2. The stockpiling effect for the two larger-share brands (53% for StarKist and 51% for Chicken of the Sea) is greater than that for the smaller-share brands (32% for 3 Diamond and 35% for the control). This is consistent with Macé and Neslin’s (2004) findings.
3. The brand-switching effect is relatively small for larger-share brands but substantially greater for smaller-share brands.
4. The consumption effect is substantial for all brands, but this effect is greater for smaller-share brands than for larger-share brands.

The comparisons imply that from a manufacturer’s perspective, the strategy of temporarily cutting prices to steal sales from other brands might not be that effective for large-share brands. Unlike in the one-period game, a larger brand’s profits could be hurt in the long run in our case because a large portion of its sales increase comes at the expense of future sales. This is because these brands have

[14]An alternative is to use elasticity decomposition. For information on how to attribute the growth of own-good demand to changes in consumers’ decisions, competitive demand, and competitive market share based on elasticity decomposition, see Steenburgh (2007).

Table 2

DECOMPOSITION OF PROMOTIONAL EFFECTS FOR ALL HOUSEHOLDS IN THE TUNA CATEGORY

	Total Promotional Effects in First Week	*Consumption Effect*	*Brand-Switching Effect in First Week*	*Brand-Switching Effect in Later Weeks*	*Stockpiling Effect*
StarKist	–1.17	–.31	–.18	–.06	–.62
	(100%)	(26%)	(16%)	(5%)	(53%)
Chicken of the Sea	–1.32	–.30	–.25	–.10	–.67
	(100%)	(23%)	(19%)	(7%)	(51%)
3 Diamond	–1.66	–.60	–.40	–.13	–.53
	(100%)	(36%)	(24%)	(8%)	(32%)
Control	–1.53	–.49	–.43	–.07	–.53
	(100%)	(32%)	(28%)	(5%)	(35%)

Notes: The numbers reported here are weighted averages at the brand level based on the sales at regular prices. The percentages relative to the total effects are in parentheses.

more brand loyals who may tend to stockpile more during promotions (we provide supporting evidence in the next section). Kopalle, Mela, and Marsh (1999) reach a similar conclusion. They show that larger-share brands can increase profits by reducing the frequency of price promotions.

Household Heterogeneity in Response to Promotions

We first investigate the impact of brand preferences on households' responses to price promotions. For each brand, we grouped the households into two segments according to their purchases at regular prices. Households in the first segment (brand loyals) purchase the focal brand at its regular price. The households in the second segment (brand switchers) consist of two types, one that purchases only on promotion and one that purchases other brands also at regular price but buys the focal brand only on promotion. To save space, we report only the weighted averages for all 12 products, weighted by their market share at regular prices. The decomposition results for these two segments appear in Table 3.

Comparison of the decomposition of promotional effects between the two segments generates the following insights:

1. For brand loyals, the majority of the increase in purchases from price promotions can be attributed to stockpiling, whereas brand switchers do not stockpile.
2. Brand loyals increase their consumption more than brand switchers.
3. Brand loyals are more price elastic (this is the "purchase elasticity" rather than the traditional price elasticity) than brand switchers because of their flexible consumption and stockpiling.

These findings indicate that it may be less beneficial for a firm with a large number of brand loyals to offer a promotion because it will lose profits from loyals not only in the current period (charging a lower price to loyals who would have bought the product anyway) but also in future periods (due to heavy stockpiling by loyals). Conversely, in a competitive market (with a high proportion of brand switchers), temporary price cuts generate the benefit of stealing sales from other brands as well as an increase in consumption at no expense to future sales. Therefore, knowing the market composition in terms of households' brand preferences will help managers decide whether it is appropriate to use price promotion strategies.

Next, we investigate the impact of household heterogeneity in category consumption preferences on households' promotional responses. We divide all households into two groups: heavy users and light users. A heavy user is a household whose total quantity purchased in all 12 weeks is above average. Otherwise, the household is a light user. Table 4 shows the decomposition results.

Comparison of the decomposition of promotional effects between the two groups shows the following:

1. Light users show a dominant consumption effect, whereas heavy users show a larger stockpiling effect.
2. Light users are more responsive to price promotions.

The smaller consumption effect for heavy users is consistent with the satiation effect. Because there is relatively flexible consumption in the canned tuna category, when induced by lower prices, light users have more room to increase consumption than heavy users (perhaps from switching consumption from other categories). The larger stockpiling effect for heavy users suggests that heavy users are more strategic in terms of planning for future consumption. The economic savings from stockpiling are more significant for this segment. This can be attributed to the different importance of the tuna category to the two groups of households and is consistent with Zhang, Seetharaman, and Narasimhan's (2007) findings.

We identified two important findings for the canned tuna category, as follows: When facing a price promotion, (1) brand loyals mainly respond with stockpiling, whereas brand switchers switch brands and increase consumption, and (2) light users mainly increase consumption, whereas heavy users stockpile more. These findings can help man-

Table 3

DECOMPOSITION OF PROMOTIONAL EFFECTS FOR BRAND LOYALS AND SWITCHERS IN THE TUNA CATEGORY

	Total Promotional Effects in First Week	*Consumption Effect*	*Brand-Switching Effect in First Week*	*Brand-Switching Effect in Later Weeks*	*Stockpiling Effect*
Brand loyals	–.90	–.27	—	—	–.63
	(100%)	(29%)	—	—	(71%)
Brand switchers	–.04	–.01	–.02	–.01	.00
	(100%)	(17%)	(63%)	(21%)	(0%)

Notes: The numbers reported here are weighted averages based on the sales at regular prices. The percentages relative to the total effects are in parentheses.

Table 4

DECOMPOSITION OF PROMOTIONAL EFFECTS FOR HEAVY AND LIGHT USERS IN THE TUNA CATEGORY

	Total Promotional Effects in First Week	*Consumption Effect*	*Brand-Switching Effect in First Week*	*Brand-Switching Effect in Later Weeks*	*Stockpiling Effect*
Heavy users	–1.25	–.32	–.23	–.07	–.63
	(100%)	(26%)	(18%)	(6%)	(50%)
Light users	–2.22	–1.28	–.40	–.11	–.43
	(100%)	(57%)	(18%)	(5%)	(20%)

Notes: The numbers reported here are weighted averages based on the sales at regular prices. The percentages relative to the total effects are in parentheses.

agers design better pricing and promotion strategies. Although a rigorous analysis of the optimal pricing strategy a firm should use under these settings is beyond the scope of this article, we provide some guidance here. In general, a firm can increase its long-term profits by discouraging brand loyals and heavy users from responding to price promotions and by encouraging brand switchers and light users to do so. For example, a firm can give price discounts on small package sizes to induce brand switchers and light users to switch. To price discriminate and discourage brand loyals and heavy users from taking advantage of these price discounts, the per-unit price of large package sizes should not be higher than the discounted per-unit price of smaller package sizes. This shows that the presence of loyals and heavy users constrains a firm's strategies in competing for light users and brand switchers.

Replicating the Analyses in Paper Towels

We have shown that in the canned tuna category, in which households are likely to be flexible in changing their consumption rates, price promotions have substantial consumption and stockpiling effects. For nonfood categories, for which the consumption rate is relatively fixed, we expect that the ability of households to increase consumption is limited, so price promotions will mainly induce them to stockpile for future consumption. To demonstrate the validity of our model, we estimate our model using household purchase data from a nonfood category—paper towels—and then conduct the decomposition of promotional effects. We employ Information Resources Inc.'s scanner panel data on household purchases of single-roll paper towels in a large U.S. city from June 1991 to June 1993. We focus on 99 households that purchased only single-roll paper towels (this may imply that the households we use in the data are relatively light users; we do not use heavy users who tend to buy paper towels in packs because modeling choices on multiroll purchases is beyond the scope of this article) and made at least five purchases during the 104 weeks. The data consist of 8714 observations, which include 1795 purchases. We group the SKUs into four product alternatives, which include the top-selling brands Bounty, Viva, and Scott (these brands accounted for 82% of total purchases), as well as other brands. The average number of rolls per purchase was 1.69, and the average interpurchase time was 8.72 weeks. The rules for data construction for paper towels are the same as those used for canned tuna. The household demographic characteristics used in the estimation are family size, income, and the employment status of the female head of household.

Table 5

ESTIMATION RESULTS IN THE PAPER TOWELS CATEGORY

Parameters	*Estimate*	*SE*
Paper towels	4.85	.01
Bounty	8.46	.01
Viva	8.07	.01
Scott	5.08	.01
Feature	.85	.03
Display	3.66	.02
Price × income	.22	.004
Price × employ	–.60	.01
c_0 (inventory)	.02	.001
c_1 (inventory × income)	.02	.002
α_{01} (power term intercept – Segment 1)	–8.18	.01
α_{02} (power term intercept – Segment 2)	–1.04	.01
α_{11} (power term family size – Segment 1)	.85	.01
α_{12} (power term family size – Segment 2)	.07	.005
Probability of Segment 1	.55	.002
σ_1 (paper towels)	6.25	.01
σ_2 (Bounty)	8.58	.01
σ_3 (Viva)	12.53	.01
σ_4 (Scott)	5.76	.01
σ_5 (feature)	.45	.02
σ_6 (display)	1.21	.01
ρ (initial inventory)	1.13	.62
ω (price updating parameter)	.14	.005
Function value	29.25	

The estimation results appear in Table 5. We use these estimates to run simulations to obtain the change in quantity purchased and consumption for all 99 households during the planning horizon of 12 weeks before and after a price cut of $.10 in the first week. We calculate the unit sales decomposition according to Equations 11–13 and 16. The decomposition of promotional effects for all households for the three brands appears in Table 6.

Consistent with what we found for canned tuna, the brand-switching effect for paper towels is lower than what most previous literature has identified—an average of 14% (with the brand switching occurring in the first week being 10%). As we expected, compared with the results from the canned tuna category, the consumption effect is much lower in the paper towels category (an average of 18% versus an average of 29% in canned tuna). The consumption effect is not zero, though the consumption of paper towels is considered relatively fixed. This could be primarily due to the category substitution effect (e.g., households might switch from cloth rags to paper towels). Alternatively, this may be due to the income effect (because of the price promotion)

Table 6

DECOMPOSITION OF PROMOTIONAL EFFECTS FOR ALL HOUSEHOLDS IN THE PAPER TOWELS CATEGORY

	Total Promotional Effects in First Week	*Consumption Effect*	*Brand-Switching Effect in First Week*	*Brand-Switching Effect in Later Weeks*	*Stockpiling Effect*
Bounty	–1.14	–.20	–.13	–.05	–.76
	(100%)	(18%)	(12%)	(4%)	(66%)
Viva	–1.04	–.19	–.07	–.02	–.75
	(100%)	(19%)	(7%)	(2%)	(72%)
Scott	–1.57	–.25	–.17	–.09	–1.06
	(100%)	(16%)	(11%)	(5%)	(68%)

Notes: The numbers reported here are based on the sales at regular prices. The percentages relative to the total effects are in parentheses.

or the notion that households are induced to use more paper towels when more inventory is on hand. Finally, the stockpiling effect (an average of 69%) is much higher in the paper towels category than in the tuna category, and it represents the majority of the impact of price promotions in this category. This is consistent with our intuition because paper towels constitute a nonfood category that is more storable than food categories.

CONCLUSIONS AND FURTHER RESEARCH

We propose a dynamic structural model to understand the impact of temporary price promotions on households' behavior and to identify the relative influences of consumption increase, brand switching, and stockpiling on the total impact. Using a hedonic approach to model a household's utility function and imposing some simplifying behavioral assumptions, we reduce the dimensionality of the problem and apply our model to a market in the presence of a large number of households and product alternatives. Our methodology helps us understand the substitution patterns among different product attributes. Our decomposition of promotional effects in the canned tuna and paper towels categories shows a much smaller brand-switching effect than what has been documented in prior research. We also find that for larger-share brands, much of the promotion-induced sales increase is attributable to stockpiling for future consumption. We then investigate household heterogeneity in terms of brand preferences and find that with price promotions, brand loyals mainly stockpile for future consumption, whereas brand switchers tend not to stockpile. We also find that in response to a price promotion, light users increase consumption more, whereas heavy users stockpile more for future consumption. These findings can help managers better design their pricing and promotion strategies.

In this article, we did not consider state dependence (i.e., households might seek variety from one purchase to another, or there may be inertia). Further research might explore the impact of price promotions when both variety-seeking (or inertia) and flexible consumption behavior are present. The consumption increase we capture in this article is more in line with total market expansion, which is different from spillover effects (e.g., price promotions of a product benefit the nonpromoted products; see Van Heerde, Gupta, and Wittink 2003). Aggregate increases in consumption at the store-level could also be due to store switchers that we do not consider in our model. Further research could explicitly model store-switching behavior and study how much of the category expansion in one store is due to store switching versus households increasing their consumption.

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